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Blast Vibration Analysis by Different Predictor Approaches-A Comparison

A. Parida*, M.K. Mishra

Mining Engineerig Department, NIT, Rourkela, India
*Corresponding Author (aprida48@gmail.com)

Abstract

Blasting is a major mechanism of rock fragmentation. Explosive usage creates ground vibration, air over pressure as well as fly rock. Blast design is a process which needs to be monitored continuously as the rock mass exhibit many vibrations within the same boundary. Often the quantum of explosive had to be determined within safe vibration limit. Artificial Neural Network approach is also gaining wide recognition for its accuracy to match with the measured values. This paper evaluates the governing relations between PPV at varying explosive quantities and distances using established approaches as well as the results by application of artificial neural network. A total of nine blast events have been analyzed. Indian Standard and ANN approaches exhibit better correlation with the measured values of PPV as compared to that by other approaches.

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Keywords: Blasting, Ground vibration, Regression Analysis, ANN

1. Introduction

Mineral resources are backbone of any industrial nation and industry needs metal and non-metals as raw material. These are extracted by both underground mining method and opencast mining method. In both cases, blasting operation is practiced to loosen the rock-mass. The primary purpose of blasting is rock-mass fragmentation and displacement of the broken rocks. The typical energy source to achieve this loosening of rock mass comes from usage of explosive. During the explosive charges large quantities of energy is released. The corresponding pressure and temperature produced during blasting are about 50 GPa at 5000K respectively [1]. There are reports that about 20% of explosive is used in actual breakage and displacement of rock mass and rest reflects in ground vibration, fly rock, noise etc.[10] Excessive levels of structural vibration caused by ground vibration from blasting can result in damage to or failure of structures. The intensity of ground vibration depends on various parameters which can be categorized into two classes-Controllable parameters and Uncontrollable parameters.

Controllable parameters are mainly related to explosive characteristics (initiation system, initiation sequence, no of free faces, buffers, explosives energy, charge geometry, loading method) and blast hole design parameters (hole diameter, hole depth, sub drill depth, hole inclination, collar height, stemming type and length, blast pattern, burden to spacing ratio, blast size, configuration and blasting direction,

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initiating system, initiating sequence, no of free faces, explosive types, explosive energy, charge geometry, and loading method) while others are uncontrollable parameters which are natural and are related to geological conditions, rock characteristic etc. Ground vibration phenomenon though undesirable, yet is an integral part of the rock blasting activities. Ground vibrations are generally quantified by means of particle velocities at particular ground locations. Currently the most widely accepted single measurement of ground vibration considered potentially damaging is Peak Particle Velocity (PPV). PPV is defined as the speed by which earth particles move or pass a particular site.

The detonation of explosive sets up intense dynamic stress due to sudden acceleration by the gas pressure on the blasthole wall. Rock brakes much easily in tension than in compression and fracture progress backward from the free surface. The strain energy due to the strain waves fragments the rock mass due to mechanisms as crushing, radial cracking and reflection breakage in the presence of free face. The crushed zone and radial fracture zone creates volume of permanently deformed rock. As the stress wave intensity loses its ability to cause any paramagnet deformation in the rock mass, strain waves propagates through the rock medium as the elastic waves, oscillating the particle through which it travels. These waves are called ground vibration waves that closely resemble visco-elastic behavior. These wave travel concentrically in all directions and diminishes due to spreading of fixed energy over a meter area away from the origin [11]. Though the waves attenuate with time and distance, yet it is enough to cause damage by causing dynamic stress that exceed the material strength.

2. Blast site description

The ground vibration phenomenon due to blasting was studied at a nearby iron ore mine. The mine is located at Koira which has an average elevation of about 560 - 630 m in northern eastern peak and 570m to 610m in south western peak and is about 100 km from Rourkela, a major industrial place of Odisha, India. The iron ore mine area belongs to Jamada-Koira valley. It exhibits a synclinorial structure, generalized as a NNE trending low plunging syniclinorium with an over turned western cross fold. The main iron ore bearing area consists of blue dust, soft and biscuit ore as well as shale iron ore. The iron ore mine follows opencast method of mining. The mine location is shown in figure 1. The excavation process consists of mechanized (drilling-blasting-shovel-dumper) opencast method with 5 to 6 active benches. The average bench heights vary between 4 and 6.5 m. The explosive used are slurry cartridges (make: IDL Explosive Ltd, brand-Energel, Supergel) that are blasted simultaneously in staggered pattern.

Fig.1. Location of the iron ore mine under investigation

3. Instrumentation and data collection

The blasting operation was monitored with seismograph (make: Instantel. Inc, Canada-Minimate plus with two geophones and two microphones). Total 9 blast event were monitored over a period of two months. The diameter of blast holes was 102mm with spacing and burden of 3 and 2.5 respectively. Each hole was charged with delay of either 17ms, 25ms, or 42ms along with DTH delay 200-250 ms in order to avoid large. The PPV data were recorded at different distances within the mine premises with respect to the maximum explosive used per delay (Table 1).

Table 1. PPV data at respective distance and explosive used

Sr. No.	Distance of instrument from	Max. Explosive per delay	PPV value as

	blast area (m)	(Kg)	Recorded (mm/s)
1.	138	22.24	4.78
2	90	22.24	9.57
3	120	22.24	8.14
4	60	13.9	9.18
5	80	11.12	5.9
6	90	13.9	3.9
7	108	19.46	2.49
8	90	11.12	3.86
9	146	11.12	1.53

4. Data analysis

4.1. Ppv prediction by multiple linear regression analysis

Multiple regression analysis is used to predict linear relationship between a dependent variable and one or more independent variable. It is based on the principle that minimized sum of squares of differences of predicted and measured value and is given by

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots\ldots\ldots + b_nx_n + \beta$$

Where, b_0=intercept, β=error associated with predictor and b_1, b_2, b_n are coefficient on the nth predictor. The multiple regression analysis was carried out to predict the vibration level at corresponding radial distance and explosive quantity. The governing relation is obtained from the regression analysis as below

$$PPV = 7.800814 + 0.855482 \times Q_{max} - 0.07454 \times D$$

Q_{max} = maximum charge per delay; and
D = distance between blasting area and seismograph position.
The predicted values of PPV were compared with that of the measured values (Fig-2). There exists a good correlation between the two approaches (R^2=0.6304) that compares favorably as discussed elsewhere [1].

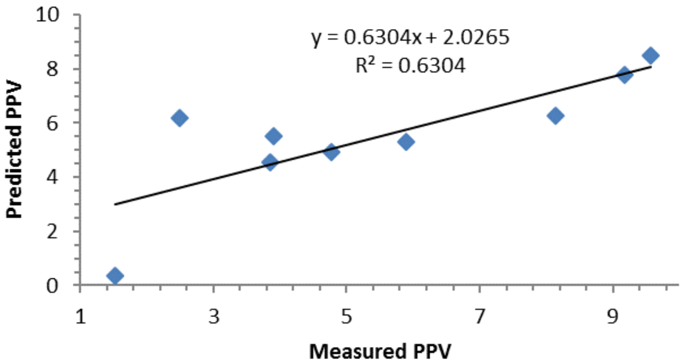


Fig.2. Predicted PPV vs. Measured PPV by MLR analysis

4.2. Feed forward back propagation neural network

ANN is the branch of intelligence science which has been introduced since 1980. Artificial neural network defined by three steps such as network architecture, training and testing [12]. The neural network has to be trained data before interpreting new information. Among all the algorithms, back propagation algorithm is very versatile and a robust technique which provides must efficient learning procedure for multilayer neural network. The back propagation neural network consists of three layers such as input layer, hidden layer and output layer. So it is called multilayer neural network. Each layer consists of a number of elementary processing unit called neurons and each neuron is connected to the next layer by weights in such a way that neurons in the input layer sends its output as input for neurons in the hidden layer. It is called forward pass. Here output is compared with measured value. The difference of error between both is called bias which proceed back through the network (backward pass) updating the individual weights of the connection and also biases of individual neurons. All the neurons in the back propagation neural are associated with a bias neuron and a transfer function. The transfer functions are step functions. Those are either linear or non linear functions designed to map a neurons' or layers' net output to its actual output. This process is repeated for all training pairs in the data till the network error reached to a minimum threshold value defined by a cost function usually the root mean squared error or summed squared error. The following algorithm is typically used for construction of neural network.

The j^{th} neuron is connected with a number of inputs as

$$X_i = (X_1, X_2, X_3 \ldots\ldots X_n)$$

The Net input values in the hidden layer is

$$Net_j = \sum_{i=1}^{n} X_i W_{ij} + \alpha_j$$

Where X_i is n^{th} no of input units;
W_{ij} is the connection between i^{th} neuron of input layer and j^{th} neuron of hidden layer; and
α_j is the bias neuron.

Usually the calculation of output in the hidden layer is determined with the logarithmic sigmoid function which is non-linear and is defined as

$f(Net_j) = \frac{1}{1+e^{-Net_j}} = O_j$,

where $f(Net_j)$ is the weighted sum of inputs for a processing unit of output layer.

In the learning process, the network is presented with pair of patterns; an input pattern and corresponding desired output pattern. The network computes output pattern by using weights and threshold value. The error at any output layer k is determined between the actual output and desired output as $e_l = i_k - O_k$

The total error is given by

$E = \sum e_l^2$

$\delta w_n = -\eta \frac{\delta E}{\delta w_n}$ descent down error surface is made using following rule for optimum weight space of the network,

Where η is the learning rate parameter; w_n is the weight of the connection between the i^{th} neuron of the input layer and the j^{th} neuron of the hidden layer; i_k is the actual output;
O_k is the desired output.

The update of the weight for the $(n+1)^{th}$ pattern is given as

$w_n(n+1) = W_n(n) + \delta w_n$

The connection between the hidden and output layer follows the similar logic. But in the above case $Net_k = \sum_{j=1}^{n} W_{jk} O_j + \alpha_k$ linear transfer function is used. Total input in k^{th} unit of output layer is given by

The predicted value by linear transfer function from k^{th} unit is

$f(Net_k) = n$

where w_{jk} is the weight between j^{th} neuron of hidden layer and k^{th} neuron of output layer; α_k is the bias neuron; n is predicted value. The process is repeated till the user specified error or epoch goal is reached.

4.3. Ann based prediction by network training

For network training, steps as initialization of weights; feed-forward; back propagation of errors and updating of weights and biases are necessary. For initialization of weights, the input parameter consists of two variables such as distance between monitoring point and blasting face; explosive and target parameter consist peak particle velocity. Each input and target parameter consists of the 9 data-set. For the training network 2-5-1(Fig-3), all 9 dataset were divided - five for the training, two for the validation and two for the testing using MATLAB (ver 2013) code. The hidden layer is made with five neurons. The training data were used for weight matrix (W) and bias vector (b) while test and validation data were used to monitor the accuracy and validation of the network. The logarithmic sigmoid function was used in hidden layer and linear transfer function was used in the output layer for function approximation. The network architecture is given in Fig. 3.

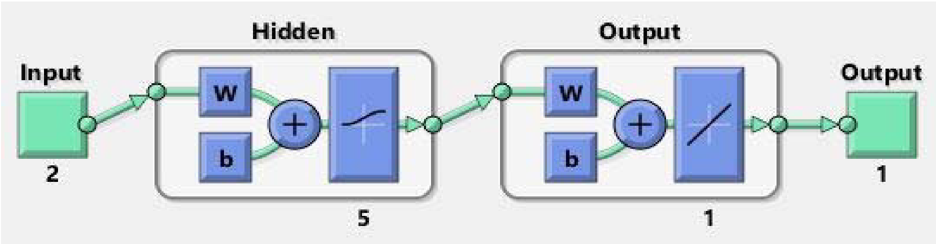


Fig.3. 2-5-1 Architecture of ANN (w and b are weight and biases respectively)

The predicted PPV values so determined from the ANN analysis were compared to that of the measured values (Fig-4). It shows high correlation coefficient (R^2=0.898).

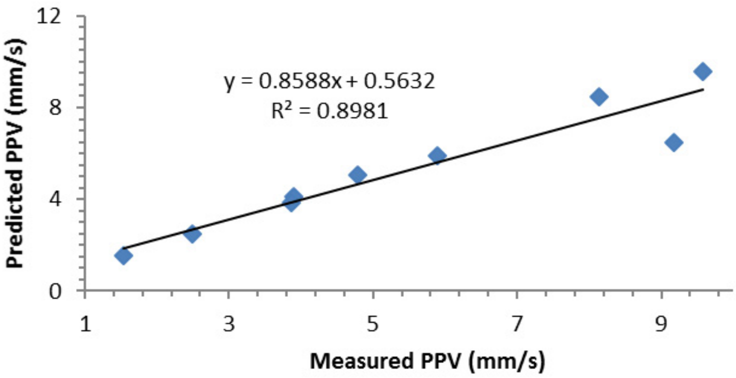


Fig.4. Predicted PPV vs. Measured PPV by ANN model

4.4. Calculated ppv by empirical equations

There exists numerous empirical equation developed from field studies discussed elsewhere [1]. Some of the popularly followed vibration prediction equations are given below (Table 2).

Table 2. Different predictor equation

Serial no	PPV Predictor Equations/Approaches	Equations
1.	USBM (Duvall and Fogelson, 1962) [13]	$\upsilon = K\left(\frac{D}{\sqrt{Q_{MAX}}}\right)^{-B}$
2.	Ambraseys–Hendron (1968) [14]	$\upsilon = K\left(\frac{D}{\sqrt{Q^{\frac{1}{3}}{}_{MAX}}}\right)^{-B}$
3.	Langefors–Kihlstrom (1978) [15]	$\upsilon = K\left(\sqrt{\frac{Q_{MAX}}{D^{\frac{2}{3}}}}\right)^{B}$

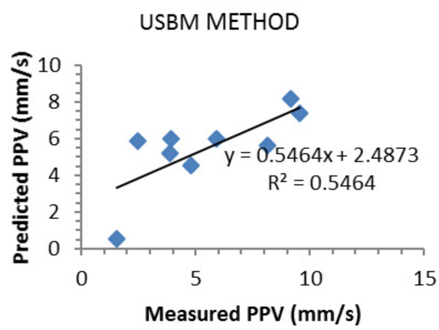
4.	Indian Standard (1973) [16]	$\upsilon = K\left(\frac{Q_{MAX}^{\frac{2}{3}}}{D}\right)^{B}$
5.	CMRI (1991) [17]	$\upsilon = n + K\left(\frac{D}{\sqrt{Q_{MAX}}}\right)^{-}$

Where υ is the peak particle velocity (mm/s) and Q $_{MAX}$ is the maximum charge per delay (Kg), D is the radial distance between blast face to vibration monitoring point (m) and K, B and n are the site constants which depends on parameters as geology of area, rock mass characteristics, etc. Regression analyses were carried out to predict the site constants K, B and n values. The analyses show that the USBM developed approach exhibit maximum correlation coefficient with R^2=0.738 and the Langferous-Khilstrom produce the minimum. The Ambraseys–Hendron and IS approaches exhibit same correlation and the CMRI is a little lower (Table 3).

Table 3. Site Constants for different predictor equations

Name of the Predictor	K	B	n	R^2
USBM (Duvall and Fogelson, 1962)	57452	2.94		0.738
Ambraseys–Hendron (1968)	2876	1.734		0.690
Langefors–Kihlstrom (1978)	7.403	2.919		0.554
Indian Standard Predictor (1973)	568.9	1.734		0.690
CMRI predictor (1991)	209.2	NA	-3.163	0.627

The five empirical equations were then used to predict the ground vibration values and predicted values were compared with the measured values (Fig -5, 6, 7, 8, 9). All the five approaches compare favorably with the best correlation coefficient exhibited by the Indian standard method (R^2=0.6851).



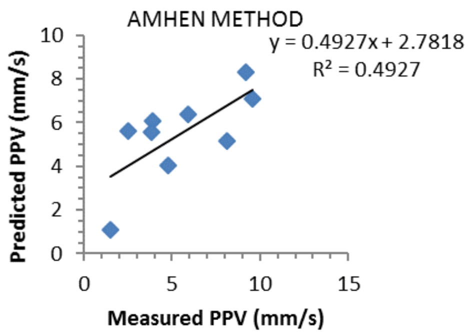
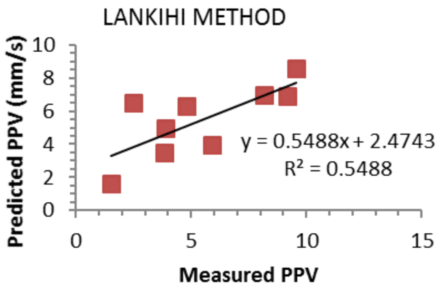


Fig.5.

Fig.6.



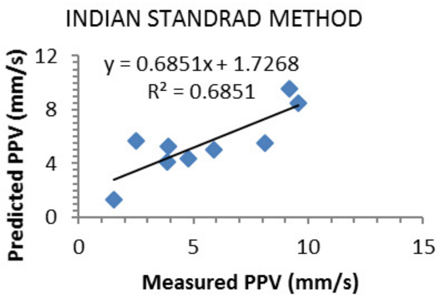


Fig.7. Fig.8.

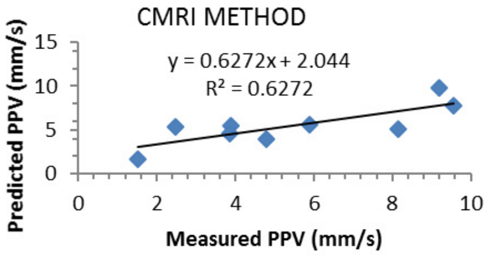


Fig.9.

Figs 5, 6, 7, 8 and 9. Measured vs. Predicted PPV by different equations

5. Results and discussion

Similar exercises between the ANN developed PPV and measure PPV values were carried out (Fig.5). The predicted PPV by ANN is much closer to the measured values as compared to MLR and other predicted value of empirical equations. The PPV values predicted by empirical approaches show either an under-estimate or over-estimate as compared to that of measured PPV values. Prediction of PPV values by multiple regression analyses are not close to the measured values as compared to that by ANN approach. Table 3 shows R^2 and root mean square error (RMSE) values for all models.

Table 3. Correlation coefficient and Error parameters

Model	R^2	RMSE
ANN	0.898	0.908
MLR	0.630	1.668
USBM	0.546	1.848
Ambraseys–Hendron	0.492	1.955

Langefors–Kihlstrom	0.548	1.844
Indian Standard Predictor	0.685	1.540
CMRI Predictor	0.627	1.676

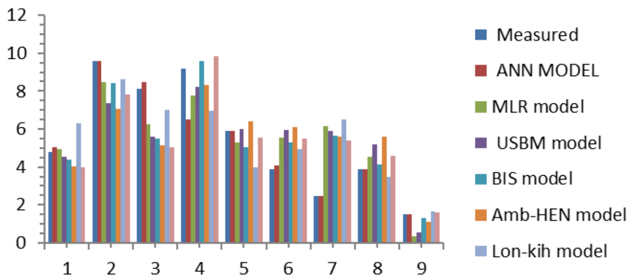


Fig.10. Comparison of Predicted PPV with measure PPV

6. Conclusions

By using back propagation ANN model with Levenberg-Marquardt training algorithm, it is concluded that ANN model is more appropriate for prediction of PPV to protect surrounding environment and structure in the iron ore mines. The parameters such as explosive and distance as input and PPV as output were considered in both cases of ANN and MLR models. MLR shows less approximation prediction PPV as compared to that by the ANN approach with the measured value. All the empirical equation shows less correlation value and more RMSE value than that by ANN approach. Hence it is concluded that the ANN approach has strong potential to predict the PPV values.

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